



Predicting Charging Demand for Electric Vehicle using Ensemble Learning as Strategy towards Smart Transportation

¹Abubakar Hassan, ²Muhammad Aji Wajiro, ³Yusuf Ayuba, ⁴Emmanuel Gbenga Dada

^{1&3}Department of Computer Engineering, University of Maiduguri, Maiduguri, Borno State.

²Directorate of Information and Communication Technology (ICT) Centre, Ramat Polytechnic Maiduguri,

⁴Department of Computer Science, University of Maiduguri, Maiduguri, Borno State

ABSTRACT

Electric vehicles (EVs) are seen as the future of the automobile industry because of their advantage of zero emissions and capability to solve the environmental and public health issues associated with conventional fuel-powered vehicles. The rapid adoption of EVs by many people around the world has led to charging demand prediction for optimal charging infrastructure planning and operation. Predicting charging demand can help enhance operations, mitigate against power outage and grid overloading, and support organisations in computing the amount of charging stations needed to satisfy demand. This paper proposes an ensemble learning model to predict the charging demand of EVs using dataset obtained from Kaggle. Four Machine learning algorithms were employed as base learners namely, Random Forest (RF), Support Vector Machine (SVM), k-Nearest Neighbour(k-NN) and Gradient Boosting Machine (GBM). Experimental results showed that SVM achieves excellent performance in comparison to other machine learning algorithms considered in the research with a MASE of 0.706. This shows that SVM is good technique for predicting EV charging demand if adopted.

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INTRODUCTION

Environmental degradation and energy deficiency has posed a great concern to the world today because of massive utilization of conventional energy sources such as fossil fuels. Statistics shows that the transportation sector is responsible for the highest CO₂ emissions (37%) in 2021, which can be significantly reduced by the adoption of electric vehicles (EVs) (Rashid et al., 2024). EVs have great advantages such as less noise, zero greenhouse gas emissions, and lower maintenance cost in comparison to internal combustion engine vehicles (ICEVs) (Rashid et al., 2024). Despite disruption of the EV supply chain by the covid-19 pandemic, EV sales reached a record high in 2021. China and Europe in 2021 had more than 85 percent of EV sales around the world. The rapid adoption of EVs has led to the huge deployment of charging infrastructures to solve EV drivers' range anxiety

but also introduces additional concerns. The power consumption of global EV fleet in 2023 was about 130 TWh of electricity, representing about 0.5% of global total electricity consumption (Rashid et al., 2024). It is projected that EVs could consume up to 2,700 TWh which is 6-8% of the total electricity demand by 2035.

The electrical power distribution system is severely impacted by the dramatic increase in EV use. The widespread adoption of EVs could severely degrade grid components and power quality. The simultaneous charging of a large number of EVs during peak hours may lead to these detrimental effects, which could be mitigated by proper charging infrastructure planning and operation. EV charging demand prediction provides the theoretical foundation for charging infrastructure planning and operation with insights into future charging patterns. As a result, it is an important research area in the smart

Corresponding author: Abubakar Hassan

✉ abubakarhassan@unimaid.edu.ng

Department of Computer Engineering, University of Maiduguri, Maiduguri, Borno State.

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city and smart transportation domains (Rashid et al., 2024; Renold & Kathayat, 2024; Shahriar & Al-Ali, 2022).

Basically, forecasting charging demand of EV can be defined as the process of computing the availability or demand status of charging stations at a point in time or given future time, by analysing past and present data on charging behaviour of EV, for instance charging session, charging duration, and charging locations, combined together with the relevant context data (Qu et al., 2024; Zheng et al., 2023). Advances in artificial intelligence (AI) especially the field of big data analytics and machine learning (ML) has shifted focus towards employing data-driven approaches to address the EV charging challenges ((Shahriar et al., 2020)). ML algorithms can be used to train and learn the trends and patterns embedded in historical EV charging demand and user behaviour data.

Predictions from the ML algorithms can be used to improve EV charging scheduling strategies (Shahriar et al., 2020)). Several research works have proven that ML algorithms are excellent for timeseries data prediction and can therefore be used for EV charging demand forecasting ((Shahriar et al., 2020)). Traditional approaches to EV charging demand analysis using qualitative techniques cannot be applied easily for practical scheduling applications. Methods such as modelling and simulation can be useful for practical applications, but have assumptions that can limit their accuracy ((Shahriar et al., 2020)). In contrast, future EV charging demand and behaviour can be predicted and used for intelligent scheduling using ML techniques. In addition, ML models employ historical data as well as environmental factors such as weather and traffic variables for accurate trend capture (Shahriar et al., 2020). In this study, an ensemble learning model is proposed using Random Forest (RF), Support Vector Machine (SVM), k-Nearest Neighbour (k-NN) and Gradient Boosting Machine (GBM) algorithms as base learners to predict EV charging demand.

This work presents the following contributions:

1. The present study involved a comparative analysis of various machine techniques, namely RF, SVM, k-NN, GBM and proposed ensemble model, in terms of their performance. The SVM model demonstrates better results compared to all other techniques with a MASE of 0.706.

2. A comprehensive examination was conducted on the outputs. The information presented in this paper offers valuable insights on the advantages and drawbacks of the proposed model.

RELATED WORKS

This section provides a brief review of research works on predicting EV charging demand in the literature. Machine Learning model based on the K-Nearest Neighbours algorithm was proposed by (Matrone et al., 2023) for predicting EV charging session duration, by assigning the event to its correct class. But the algorithm considered few variables and validated on small dataset.

Lu et al., (2018) presented a prediction approach for EV charging load using the random forest algorithm (RF). However, the algorithm was applied only on Shenzhen actual charging data and application scenarios. Almaghrebi et al., (2020) employed three different machine learning models namely XGBoost, Random Forest (RF) and Support Vector Machine (SVM) for EV charging demand prediction after a charging session starts. The experimental results demonstrated that XGBoost, slightly outperforms the other algorithms used with an RMSE equal to 6.68 kWh and R2 equal to 51.9%. But the dataset does not consider environmental variables such as weather and traffic.

Almaghrebi et al., (2024) Proposed a new technique for robust and real-time forecasting of key charging behaviours. Machine learning models namely Random Forest (RF), XGBoost and Artificial Neural Network (ANN) were trained for forecasting the duration of connection and charging, charging demand, and time up to the next charging session employing historical data and specific behaviours of users. However, the dataset did not contain environmental factors such as weather and traffic variables.

Shahriar et al., (2021) proposed ML models namely random forest, SVM, XGBoost and deep neural networks for charging behaviour prediction of EV using historical charging data in conjunction with weather, traffic and events data to predict EV session duration and energy consumption. Despite this, the dataset is limited to events in a university campus. Rathore et al., (2023) presented EV energy consumption prediction method using the historical charging data and four (4) popular machine learning (ML) techniques such as Random Forest, XGboost, ANN and DNN. Random Forest model achieved the best predictive results followed by XGboost. However, environmental factors such as weather and traffic variables were not considered.

Akshay et al., (2024) proposed time series models for predicting the charging stations electricity demand. The Seasonal Auto Regressive Integrated Moving Average (SARIMA) model achieved superior performance compared to the Autoregressive Moving Average (ARMA) and Auto Regressive Integrated Moving Average (ARIMA) models. However, the dataset does not consider environmental factors such as weather.

Hybrid strategy was proposed by Jeon et al., (2022) for EV charging demand prediction using ARIMA model and ML techniques. Experimental results illustrated that the ML models proved superior to the traditional statistical models used. However, relatively small dataset was considered. Vishnu et al., (2023) presented three learning models for short-term EV demand forecasting including Auto-regressive (AR) forecasting, support vector regression (SVR), and long short-term memory (LSTM). LSTM obtained the best performance with a mean absolute error (MAE) of 4 kW and a root-mean-squared error (RMSE) of 5.9 kW. The study only employed adaptive charging network (ACN) data between April 2018 and January 2019.

It was clear that based on the related works reviewed, there is no any research work reported in the literature that proposes ensemble machine learning approach for EV charging demand prediction using RF, SVM, k-NN and GBM as base learners.

Table 1: Summary of Related Works

Author & Year	Technique Used	Dataset	Advantage	Research gap
Matrone et al., (2023)	k-NN	MyElectric Avenue Dataset	Better performance compared to traditional statistical models	Limited dataset and environmental factors not considered
Lu et al., (2018)	RF	Shenzhen charging dataset	Better performance compared to traditional statistical models	Limited dataset
Almaghrebi et al., (2020)	RF, XGBoost and SVM	Nebraska State Dataset	Better performance compared to traditional statistical models	Environmental factors such as weather and traffic not considered
Almaghrebi et al., (2024)	RF, XGBoost ANN	Omaha Dataset	Better performance compared to traditional statistical models	Environmental factors such as weather and traffic not considered
Shahriar et al., (2021)	RF, SVM, XGBoost & deep neural networks	ACN Dataset	Better performance compared to	Limited dataset

Corresponding author: Abubakar Hassan

✉ abubakarhassan@unimaid.edu.ng

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Author Year	& Technique Used	Dataset	Advantage	Research gap
Rathore et al., (2023)	Random Forest, XGboost, ANN and DNN	ACN Dataset	traditional statistical models Better performance compared to traditional statistical models	Environmental factors such as weather and traffic not considered
Jeon et al., (2022)	ARIMA model and ML	Korean Environmental Corporation Dataset	Better performance compared to traditional statistical models	Limited dataset
Vishnu et al., (2023)	AR, SVR, and LSTM	ACN Dataset	Better performance compared to traditional statistical models	Limited dataset
Akshay et al., (2024)	SARIMA, ARMA and ARIMA	Colorado Dataset	Better performance compared to traditional statistical models	Environmental factors such as weather and traffic not considered

METHODOLOGY

This section discusses the dataset, machine learning algorithms used and the ensemble learning architecture proposed. The experiment is carried out in Python Jupyter Notebook environment where the ML predictive models were trained and tested using dataset obtained from Kaggle.

Dataset Description

This study uses the EV Charging Dataset obtained from Kaggle that records real-world E charging behavior and patterns across various locations. The dataset contains 26 key features, each providing valuable insights into the operational and environmental factors that influence EV charging loads. The features include vehicle-specific data, charging station details, and environmental metrics.

Random Forests (RF)

Random forest (RF) is an ensemble model which combines multiple decision trees. By randomly selecting samples and features, RF reduces the correlation between decision trees, drawing a random and uniform sample size from the original training data. It extends decision trees

such that multiple decision trees are combined and applied to various subsets of the input data to accomplish prediction tasks. As a result, the final output is computed by taking the average of the predictions of all decision trees in the ensemble in case of regression problems (Hassan, Abatcha, et al., 2024; Marzbnai et al., 2023; Mienye & Sun, 2022; Rashid et al., 2024).

The implementation of the RF algorithm can be outlined as follows:

1. Start with a root node that corresponds to the entire dataset.
2. Identify the optimal attribute to split the data at the current node.
3. Next, one branch is created for each possible value of the selected attribute, and the data is split accordingly.
4. Repeat steps 2 and 3 recursively for each child node until a stopping criterion is satisfied.

Support Vector Regression (SVR)

SVR came from statistical learning theory in the 1990s which is an extension of the Support Vector Machine (SVM) model. The whole essence of the SVR is to minimize the error generated by fitting the model to data using a

Corresponding author: Abubakar Hassan

✉ abubakarhassan@unimaid.edu.ng

Department of Computer Engineering, University of Maiduguri, Maiduguri, Borno State.

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hyperplane that is placed closely to each point. This is to ensure that all points are within a given distance from the hyperplane (Marzbnai et al., 2023).

K-Nearest Neighbor(k-NN)

K-NN is a machine learning algorithm that does not require parameter estimation for solving both classification and regression problems. K-NN computes the distance between data points using distance measures such as Euclidean distance and predicts the output value for a given data point by averaging the values of its k-nearest neighbours (Hassan, Ayuba, et al., 2024; Marzbnai et al., 2023). The steps of the K-NN regression can be listed as follows:

1. Select the number of K nearest neighbours to be taken into account.
2. Compute the pairwise distance between the input sample and all the samples in the training data set.
3. Pick the K samples from the training set that have the smallest distances to the input sample.
4. Calculate the mean value of the K nearest neighbours that were determined, and assign it as the predicted value for the input sample.

Gradient Boosting Regression (GBR)

Gradient boosting iteratively chooses a function that opposes the gradient direction in order to optimize a cost function over the whole function spaces. It uses gradients to identify deficiencies in subpar models using an iterative approach to finally combine base learners for minimising the prediction errors (Dada et al., 2022). The framework of the Gradient Boosting Machine (GBM) can be summarised as follows:

1. Subsample rows of samples from the dataset was collected before creating each tree.
2. Subsample columns of samples from the dataset collected before creating each tree.
3. Subsample columns of samples from the dataset which was collected before considering each split in each tree.
4. Output the result of the predicted values.

Proposed Approach

Ensemble learning is a machine learning approach that combines predictions from two or more base models to achieve superior results and better generalization by leveraging on the advantages of different base models. This is motivated by the fact that machine learning algorithms have shortcomings and can make errors. Ensemble learning methods are broadly grouped into boosting, bagging, and stacking (Dada et al., 2024; Mienye & Sun, 2022).

This study employed stack ensemble learning (SEL) algorithm to predict EV charging demand. The stacking algorithm architecture incorporates four base learner models: Random Forests (RF), Support Vector Machine (SVM), k-Nearest Neighbors(k-NN) and Gradient Boosting Machine (GBM). In addition, it includes a voting regressor meta-learner that combines the predictions from the base algorithms. The level 0 models serve as the foundational models, while the level 1 model functions as the meta-model. The stacking ensemble algorithm comprises the initial training data, primary level models, primary level predictions, secondary level models, and the final prediction. Figure 1 illustrates the block diagram of the proposed stacking ensemble learning architecture.

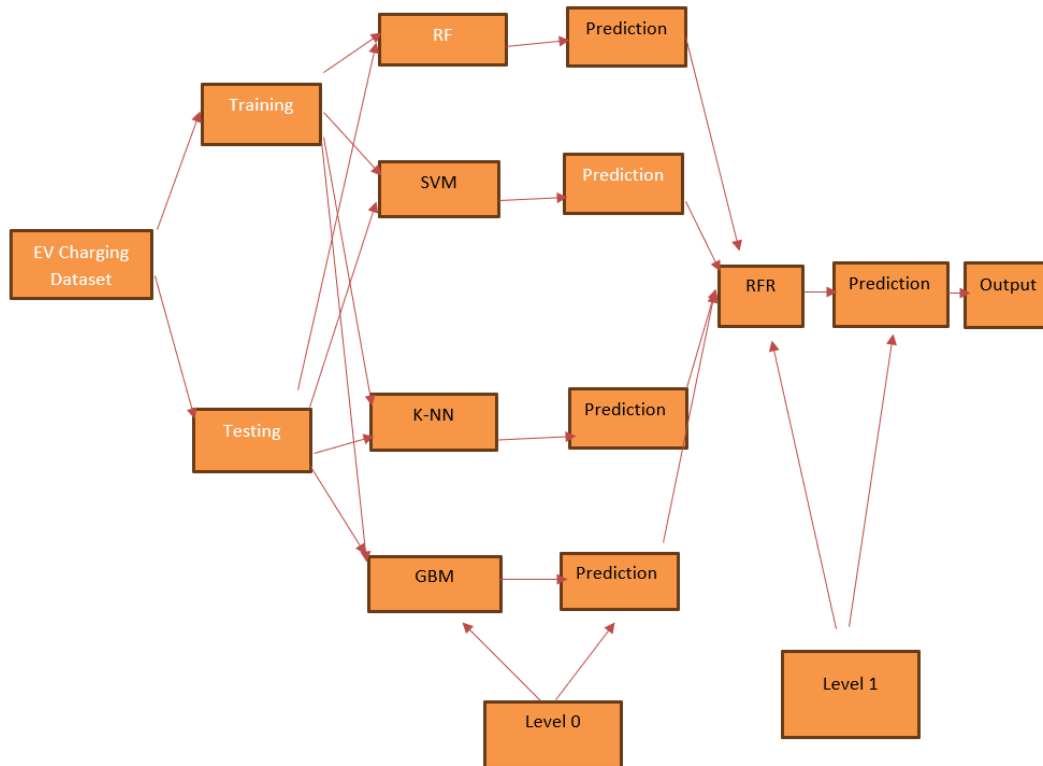


Figure 1. Proposed Ensemble Learning Architecture

appropriate values for each weight and bias parameter based on labelled samples. These factors play a crucial role in refining the effectiveness of the model.

Experimental Settings

The experimental and parameter settings for the study are shown in Table 1. The process of training a model entails the selection of

Table 1. Experimental Settings and Parameter Tuning of RF, k-NN, SVM, GBM and the Ensemble model.

Model	Hyperparameter	Values
RF	n_estimators	100
	random state	42
k-NN	n_neighbors	5
	kernel	rbf
SVM	C	1.0
	epsilon	0.1
GBM	n_estimators	100
	learning rate	0.1
	max_depth	3
	random state	42
Ensemble	n_estimators	100

Corresponding author: Abubakar Hassan

✉ abubakharhassan@unimaid.edu.ng

Department of Computer Engineering, University of Maiduguri, Maiduguri, Borno State.

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Performance Metrics

The prediction performance of the proposed ensemble model and the machine learning algorithms were evaluated using three metrics: Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Scaled Error (MASE). MSE is defined as the average of the squares of the error difference between predicted and actual values in the test.

$$MSE = \frac{1}{n} \sum_{n=1}^n (I_n - \tilde{I}_n)^2 \quad (1)$$

RMSE is defined as the standard deviation of prediction errors in a test.

$$RMSE = \sqrt{\frac{1}{n} \sum_{n=1}^n (y_n - \tilde{y})^2} \quad (2)$$

MASE is defined as a measure of the accuracy of predictions that represents it as a percentage in comparison to a standard mean error.

$$MASE = \frac{1}{n} \sum_{n=1}^n \frac{|y^n - \tilde{y}^n|}{\frac{1}{n-m} \sum_{n=m+1}^n |y^n - \tilde{y}^n|} \quad (3)$$

RESULTS AND DISCUSSION

This section presents the results and examines the significant discoveries derived from our simulations. The experiment was carried out in Python Jupyter Notebook. Figure 2-6 present the time series of all the machine learning compared in this study, which consists of actual EV charging demand and predicted EV charging demand.

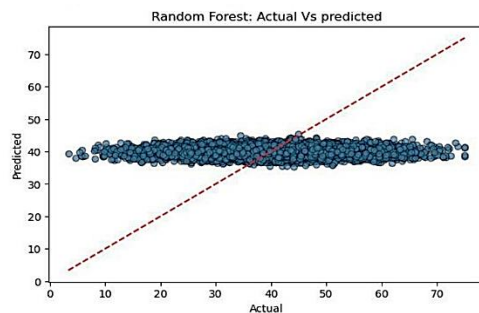


Figure 2. Charging Demand Prediction using RF

It can be seen that the predictions using RF algorithm that predicted and the actual values cluster around with MASE of 0.71194 which illustrate close association.

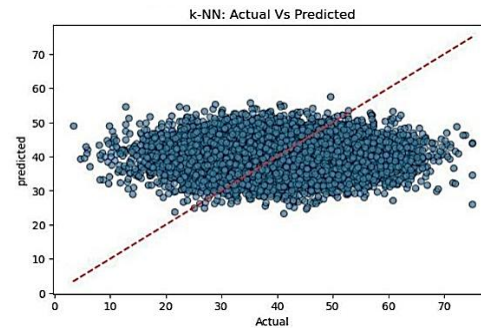


Figure 3. Charging Demand Prediction using k-NN

It is evidently clear that there are significant variations the predicted and the actual values using k-NN algorithm and an MASE value of 0.7774 was obtained.

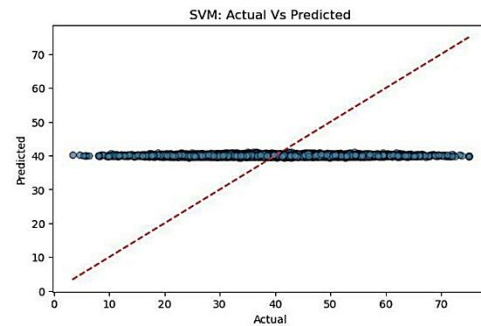


Figure 4. Charging Demand Prediction using SVM

There is significant correlation between the predicted and the actual values using SVM algorithm as the values cluster more closely with an MASE value of 0.70610.

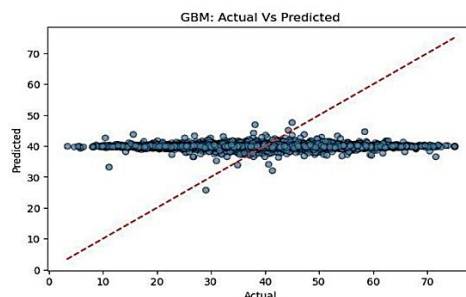


Figure 5. Charging Demand Prediction using GBM

Corresponding author: Abubakar Hassan

✉ abubakarhassan@unimaid.edu.ng

Department of Computer Engineering, University of Maiduguri, Maiduguri, Borno State.

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Predictions using GBM model illustrates a good performance as the actual and the predicted values cluster around each other which indicates significant association.

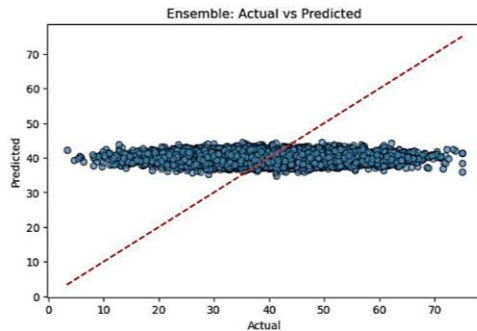


Figure 6. Charging Demand Prediction using Ensemble Model

The proposed ensemble model shows a relatively good performance as it can be seen that the predicted and the actual values cluster around each other but not so closely as SVM and GBM. About 80% of the EV charging dataset was used for training the models while the remaining 20% of the dataset was used for testing. Three performance metrics were adopted in this paper, which were RMSE, MSE, and MASE. Table 2 displays the statistical results of all the machine learning models considered in this paper. SVM performed excellently with a MASE of 0.7061, followed by GBM with a MASE of 0.7063. The reason for superior performance by SVM and GBM models could be due to their robustness and successes in regression and classification problems. The k-NN performs the least among the models used in the study.

Table 2: Performance Comparison of The Machine Learning Models on EV Charging Demand Dataset

Model	RMSE	MSE	MASE
RF	10.10689	102.1493	0.71194
K-NN	10.9932	120.8512	0.7774
SVM	10.01896	100.3796	0.70610
GBM	10.0250	100.50089	0.7063
Proposed Ensemble	10.09798	101.9693	0.7124

The reason why SVM algorithm performed better than the proposed ensemble could be due to its great performance in regression and classification problems and applications.

CONCLUSION

An ensemble learning model has been proposed for predicting the charging demand of EVs using dataset obtained from Kaggle. Four Machine learning algorithms were employed as base learners namely, Random Forest (RF), Support Vector Machine (SVM), k-Nearest Neighbour(k-NN) and Gradient Boosting Machine (GBM). Simulations results illustrated that SVM achieved superior performance than the proposed ensemble model and other machine learning

algorithms considered in this study. The findings derived from this paper demonstrate that SVM is a promising model that can be employed for EV charging demand prediction. Future work should consider improving the prediction performance of SVM by integrating soft computing and computational intelligence techniques such as Whale Optimization Algorithm (WOA), Moth Flame Optimization (MFO) algorithm, Grey Wolf Optimization (GWO) algorithm and Firefly algorithm (FA). The key findings of the study was that SVM achieved superior performance followed by GBM model in comparison to the proposed ensemble and the other model employed in the study. This could be due to great success of the two models in regression and classification tasks.

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Corresponding author: Abubakar Hassan

✉ abubakarhassan@unimaid.edu.ng

Department of Computer Engineering, University of Maiduguri, Maiduguri, Borno State.

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Corresponding author: Abubakar Hassan

✉ abubakharhassan@unimaid.edu.ng

Department of Computer Engineering, University of Maiduguri, Maiduguri, Borno State.

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